BLOW-MOLDING PROCESS AUTOMATION USING DATA-DRIVEN TOOLS

by

Prabhjot Kaur Luthra

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Abstract

With the increasing demand for goods in today's world with its ever-increasing population, industries are driven to boost their production rate. This makes issues of process optimization, maintenance, and quality control difficult to be carry out manually. Furthermore, most industrial sectors have a plethora of data acquired everyday with very little knowledge and ideas to handle it most effectively. Motivated by these considerations, we carry out a study in process automation using data-driven tools for a manufacturing process intended to produce high-quality containers. The first task involved studying the process, building and proving a hypothesis through data collection from experiments and the production line. Our hypothesis was the linear correlations between various sensor variables from our physical understanding of the process. We developed an automated process flow, i.e., a so-called Digital Twin (a numerical replication of entire process) for this process to enhance the analytical and predictive capabilities of the process. This showed similar predictions when compared to static models. An automated in-line quality control algorithm was also built to remove the manual component from this task, using state of the art computer vision techniques to utilize the power of data in the form of images. Lastly, to further provide the process engineers with predictive power for maintenance we carried out a few proof of concept projects to show the competence of such tools in minimizing costs and improving efficiency on the shop floor. All studies carried out showed great results and have immense potential to methodically use data to solve some of the pressing problems in the manufacturing sector.

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Introduction

1.1 Introduction

When J. Presper Eckert and John Mauchly began the construction of ENIAC, or what would be known as the first-ever "computer" in 1943, no one could foresee the potential of such a machine which is essential for any business in the 21st century. Starting from a few hundreds of computations per second on the ENIAC in the 1950's, today Fugaku, one of the most powerful supercomputers can perform 442 quadrillion calculations per second. Such a huge boost in processing technology in less than half of the century opens up so many possible paths in each sector of daily life. Information Technology industries has been at the top of the list for the last decade using big data analytics for better decision making. Today as part of "Industry 4.0" (more on this in the later sections) even process industries from pharmaceuticals to product manufacturing are taking a step towards the digital transformation to make better and efficient decisions from processes to operational tasks. Chemical processes are not easy to model or control, physical modeling requires a number of assumptions and data-driven models could be the answer to some of these limitations. Chapter 1 sets the stage for the importance of the work done till now in process automation while the projects carried out for blow-molding process automation are explained in detail from Chapter 2 - 5.

1.2 Hidden Industrial Treasure: Data Explosion

In the last decade, we have seen a data explosion in industries. By the year 2020, stored data was estimated to be 44 zeta-bytes which is almost triple the amount accumulated since 2010. The worldwide cache of data shows a compound annual growth rate of 61% when compared to less than 1% for world population growth by 2025. Presently, more than 80% of the data is unstructured and most industries are building ”big data” analytical platforms to gain deeper insights and find hidden trends in this huge pool of data (Milenkovic (2019)). Manufacturing Industries produce gigabytes of data every week from corporate business level (sales, production units, HR, logistics, etc.) to unit level (process variables, maintenance records etc.). Recent reports highlighted that ”the hidden treasure” of most industries is now **data** which used to be **patents** owned by the firm. The Internet of Things (IoT) and Digital Twins are the upcoming tools that can revolutionize industry by providing a huge boost in process, logistics and sustainability efficiency resulting in an increase in economic profits. The IoT is an emerging technology that is already a part of our lives from smart phones to smart homes. This ensures the connection of electronic devices and sensors through the internet, and ease of interaction with the user to make their lives easier. Kumar, Tiwari, and Zymbler (2019) describes a multitude of application areas from traffic management to smart waste collection systems. Along with great potential, it brings along with itself a number of challenges from its application areas to environmental and social impact. Howsoever well-constructed and efficient are the models in making sense from the data explosion, it is hard for a number of people to accept such changes and go on the path of data-driven decision-making. Security and privacy are other major concerns if we go down this path. But on the bright side, many firms have adopted this methodology and have had great results which are described in the next few sections.

1.3 Industry 4.0: Next Step in the Industrial Revolution

Th industrial revolution took birth with the invention of steam engine, and rapidly standardized in its second phase. The third Industrial Revolution aimed at increasing the efficiency of the manufacturing processes through the invention of machinery. In the past few years, automated machines and robots have revolutionized production processes achieving minimal human contact. But real-time decisions on safety, process control, and maintenance still require human intervention. With increasing amounts of data stored every day in such industries, as part of the fourth Industrial Revolution, firms are shifting to utilize the power of data as knowledge through data-driven tools that are no longer restricted to the IT sector. The concept of Industry 4.0 took birth in Germany in 2011, where the government was created huge initiatives to computerize the manufacturing process. The work was carried further by the "Working Group" and, in the 2013 "Hannover Fair" this firm presented it's final strategy to go down this path. Today, this concept is applied by various industries all around the world each coming up with their own strategies to adapt to this changing trend. From the past few years, "capital-intensive" manufacturing plants have focused on engineering knowledge and conventional statistical tools for "Advanced Process Control" (Qin, Liu, and Grosvenor (2016)). These tools require a lot of effort in terms of both labor and time, and often work well for simple processes. But, with high demand, the processes are becoming more complex with data coming from various sources that urges these industries to adopt more advanced tools. The deep insights that analytical platforms provide not only to reduce the costs and improve the processes by a huge margin, but the adaptability of these tools makes them a viable option to extend to various products, lines and plants worldwide.

1.4 Digital Twins is not just a concept: Industrial Case Studies

"Industry 4.0" works on the motto of computerizing the manufacturing process through automated tools and utilizing the power of "big data", so that process engineers have the capability to run and observe the plant from anywhere in the worlds, especially useful in situations in which the plant capacity is decreased, as happened this year during the pandemic (2020). One of the tasks employed in this regard is to develop a "Digital Twin" which is defined as "a digital representation of the production systems and processes using collected data and information to enable analysis, decision-making, and control for a defined objective and scope" Shao and Helu (2020). It is estimated that, by the year 2025, most of the manufacturing industries will have at least one Digital Twin deployed. The use of these Digital Twins needs to be specified before one goes down this route either to decrease the downtime, optimize the production and maintenance schedule using shop floor data, or monitor and control process equipment. Haag and Anderl (2018) provides a compelling proof of concept example for the calculation of force exerted on a beam due to the displacement of linear actuators, both from a physical and digital twin, wherein the latter was a CAD simulation and both were connected by data flow to each sides through prediction dashboards. This is a very simple idea by which simulations are an estimated representation of the experiments, where they can either be driven-by physical equations, like the CAD models, or are more data-driven using AI and ML. A number of companies have adopted these products, some of which are listed below as examples of successful case studies that have deployed "Digital Twins":

- In 2017, Lamborghini collaborated with KPMG to build tools for production automation. As a new model was getting launched, KPMG developed complex IT platforms to monitor processes from assembly to finished products on the floor. An automotive line has many moving parts, controlled by numerous sensors, and through these tools it was easy to monitor even the most intricate processes from remote locations and take appropriate actions. With the advent of computer vision tools, automated guided vehicles (AGVs) now do not require any human interference for moving parts around the plant. Today, what started as a strategy for this business, now provides immense economical profit and high yield processes overall different products. (KPMG (2020)).
- In 2016, General Electric launched Predix APM (Asset Performance Management System) which is a software platform for maintenance and operations management on the shop floor. This characterizes the associated risks, operating scenarios, and system configuration to come up with a schedule and a good estimate of the downtime,

operating and maintenance costs, etc. These simulations are used to create a strategy for asset and process optimization. There are three cores of APM: SmartSignal, APM Health and APM Reliability which monitors the health of the systems and equipment and sends out a signal to the operators and plant managers depending on the nature of these faults and risks. With advent of the Covid-19 crisis, many oil-and-gas industries have deployed similar platforms to reduce the operating and maintenance costs due to line shutdown issues (G. Digital (n.d.)).

- Siemens also has launched and deployed its Digital Twin software for various applications. Recently, Siemens not only launched an alternative way of transportation as an electric car called 'Solo' from "Electra Meccanica", a Canadian start-up company, but the entire design and manufacturing of this product was performed through Digital Twin software along with testing and maintenance in the production of various components. More recently, a Californian company called "Hackrod" also utilized this software for the production of a futuristic lightweight form of a chassis for a prototype of a race car. Most of these projects were done to replicate their products through physics-based modeling and simulation, and more recently have incorporated the use of "big data" for Siemens to be an Industry 4.0 pioneer (S. Digital (n.d.)).

- IBM has launched its own Digital Twin Technology called Watson IOT Technology, which has been used by various industries, one of which is the Port of Rotterdam which aims at using these tools to build a "Digital Port" by the year of 2030. This port has been progressive and expansive in its approach since the beginning of the project to accommodate all types and sizes of sailing vessels. Under the Port Vision 2030 plan, it plans to use a plethora of data coming from various sensors including air, humidity, geospatial locations, etc., analyze it in order to optimize the supply chain routes for various large organizations, manage its operations by planning the loading and unloading quantity in a cost-effective manner, etc. Such a novel approach to track real-time data from any corner of the world provides various companies optimized and safer routes for payloads and cargo ("How the Port of Rotterdam is using IBM digital twin technology to transform itself from the biggest to the smartest." (2019)). This is just one of the examples, more broadly, the Watson IOT has shown compelling advantages as a "Digital Twin" in multiple sectors (Watson (n.d.)).

1.5 Quality 4.0: Intelligent Total Quality Management

For small and mid-size companies, it is often difficult to employ multiple personnel on the line for activities like process control. Quality Control is one such potential area where the manual intervention to take out random samples from the line and perform quality checks beyond visible features, like dimensions, like crystallinity, weight, opaqueness, strength, etc., could be replaced . This manual interference is both time- and labor-consuming, as well its tendency to lead to discrepancies as some of the qualities are subjective, hence the output would vary from person to person. To tackle this issue, Industry 4.0 involves the process of replacing these labor-intensive processes with automated tools which, more recently, are utilizing the power of data to do these quality checks. Albers, Gladysz, Pinner, Butenko, and Stürmlinger (2016) came up with a strategy to make the quality control a consistent process by developing a set of questions which are asked to the operator regularly. The data so-collected is analyzed and presented as insights to stakeholders for a broad overview. But this is just a very small step. A more advanced technique was presented by Bahlmann, Heidemann, and Ritter (1999) where they used Artificial Neural Networks for quality checks on the line based on a number of parameters collected by sensors and images. They showed how the implementation of such a system could potentially reduce the costs of manufacturing to a great extent as well as making quality control a consistent process.

1.6 Future of Operations and Maintenance

Most maintenance procedures on the line are carried out in two ways either through preventive maintenance where a maintenance schedule in place for the equipment, or react to failure strategy where the maintenance is done when the equipment fails, which isn't followed extensively today but in certain instances performed on the line. Industry 4.0

brings with itself predictive maintenance. The underlying assumption of this strategy is that all the equipment are connected to the internet and hence can communicate with each other. Through the massive amounts of data collected, we can detect patterns related to this propagation of errors between equipment and alert the necessary personnel before an apocalyptic situation presents itself. Melo (2020) lists down various key components to carry out PdM like big data, IOT, artificial intelligence, cyber physical systems etc. Some of the case-studies in this area are listed below. More on PdM will be discussed in Chapter 4.

- C3 AI is one of the biggest AI firms in the US. Their product C3 AI CRM for Manufacturing provides AI-enabled capabilities to manufacturing industries to automate their operations as well utilize comprehensive sales, marketing, and customer experience data for better operations and supply chain logistics decision making. A cloud-based approach such as this on, say, Microsoft Azure and Adobe Cloud platforms helps stakeholders, allows plant managers and operators to monitor operations on the line from any corner of the world (AI (n.d.)).

- Falkonry is a more recent platform for predictive operations excellence. The products produced by this firm help multiple industries in various sectors from pharmaceutical, mining, semiconductors to manufacturing plants for multiple applications like process optimization, yield improvement, safety and compliance, etc. One of the use-cases so listed helped the oil and gas industries to predict compressor failure for fuel gas operations six weeks before it occurred solely with respect to the sensor data collected, thus reducing downtime from 36 hours to a few hours (Falkonry (n.d.)).

1.7 Overview of Chapters

Our work here aims at taking a step towards Industry 4.0. The objective was to utilize gigabytes of data generated monthly from the manufacturing process for blow-molded containers, to get deeper insights about the quality of the process data, attain a deeper physical understanding of the process by monitoring the casual relation between variables, optimize and control the process, identify and analyze the fault conditions, work towards predicting faults for optimizing maintenance schedules, etc. The work was carried out as multiple projects over the past few months, some of them are covered in detail in the following chapters.

Chapter 2 gives a brief overview of the blow-molding process that we were trying to automate, the complexities are mentioned but intricate details are proprietary to the firm. Here we also describe the approach we took to build a "Digital Twin" of our process using "Gaussian Bayesian Networks". The mathematical proofs and the development of the models are also explained through experimental and statistical results. Furthermore we used this network structure for the process as the foundation to develop a fault detection and root cause analysis algorithm.

Chapter 3 gives a brief overview of a patent we published recently for another application of data driven tools for inline quality control using computer vision techniques. The chapter begins with laying out the problem statement and the experiments which were conducted to obtain an image data-set. This data-set was then used to build a Convolution Neural Network model which was used to automate the classification of products as good or bad, thus a faster and more efficient alternative to manual quality check.

Chapter 4 gives a brief overview of the Predictive Maintenance proof of concept projects we carried out to enhance the predictive capabilities on the line to diagnose faulty equipment. This is another application of the data-driven tools as part of Industry 4.0. Here we describe various ways to utilize sensor data or human recorded data as maintenance records to correctly predict the faulty equipment and time when they will fail.

Chapter 2

Predictive Modeling using Gaussian Bayesian Networks

2.1 Introduction

With the coming of Industry 4.0, one of the biggest objectives has been to develop replicated digital models of the entire process. In order to gain a deeper understanding of processes both for optimization and control of the process, one either needs to spends hours on the process or develop an estimated physical model. Each has its own disadvantages, the former is very time-consuming while the latter needs an in-depth physical understanding and great expertise in this area. In addition, such models make a number of assumptions to simplify the process which may or might not hold true. Another hybrid approach is to develop such a predictive capability of the process using data-driven models. With the data explosion in this sector, and the pressing need to utilize ”mountains” of data, most data-driven approaches are preferred today (Munirathinam and Ramadoss (2016)). Our objective in this project was to develop such a data-driven model to correctly characterize the process to gain a deeper understanding of the process, relations between variables as well as use such models as the foundation to design recommendation and fault diagnostics systems.

2.2 Manufacturing Process for High Performance Containers and Problem Introduction

Injection stretch/ blow-molding is a very well-known process for the product commonly known as PET (Polyethylene Terephthalate) containers. This large-scale plastic container manufacturer has its own patent (Silvers, Schneider, Bobrov, and Evins (2015)) of designing the process in order to achieve enhanced thermal properties in containers, i.e., to exhibit similar properties to glass. The production of such PET containers is a three-step process: i) the melt PET resin is injected into a preformed mold (an extrusion and injection process), ii) the amorphous preform so produced is heated above the glass transition temperature (Tg) for selective spatial crystallization, iii) this partial crystalline preform is inflated using a stretch rod to obtain the desired container shape. In the last step, there are two steps: (1) stretching, i.e., increasing the height of the preform and (2) blowing, i.e., introducing compressed air to increase its width. Each step involves some critical parameters which needs to be monitored closely and needs to be optimized to produce containers of the desired quality and dimensions (Schmidt, Agassant, and Bellet (1998)).

PET is an interesting choice of a thermoplastic polymer for producing glass-like containers as it exhibits both amorphous and crystalline phases which can be explained by a two-phase or a three-phase model. In the two-phase model, there is the amorphous phase in which there is random or chaotic nature of the molecules mostly in the molten state of PET. While in the crystalline state, there is an ordered alignment of molecules in certain directions and there is a possibility of folding into lamellae which introduces opaqueness in the formed product. But the objective is to obtain a transparent container with a crystalline-like nature of the molecules for enhanced properties. Hence, the three-phase model was introduced. As the name suggests, there are three phases: a mobile amorphous phase, a rigid amorphous phase and a crystalline phase. The addition of the rigid amorphous phase introduces order or crystallinity into the PET molecules without the introduction of opaqueness. In our process, this phase is achieved using stain- induced crystallinity wherein, under suitable heating and stretching ratios, the molecules are oriented in the desired direction. The innovation in the process comes from the introduction of a preferential heating process at preferred locations which is performed to optimize the material distribution and rigid amorphous phase once stretched and blown. The process parameters, in this case play a crucial role as there are several metastable states possible (during thermal annealing it can even reside in a completely crystalline phase or the mobile rigid phase or a combination of all three) and the process variables have to be optimized to achieve the desired state wherein the transition to the completely crystalline phase is a very slow process and does not introduce anomalies like shrinkage once removed from the molds (Silvers et al. (2015)).

PET blow-molding is such a complex and precise process that a deeper understanding, requiring predictive capability and control, is needed to make sure the produced containers have the desired shapes and specifications. To accomplish this goal, we started the process by exploring the data set consisting of sensor signals from various sources, including the temperatures at the heated zones in the preform, the stretching rod position and speed, the mold both for preform and container parameters, etc. Then, in order to understand and quantify the hypothesized correlation between variables, we designed various experiments starting from Aspen Fluent simulations to narrow down the range of the parameters, single mold experiments with location- mapping to understand the stretch/blow process , and lastly experiments in the real-life scenario, i.e., on the production line to characterize the process noise. After gaining deeper insights and to move from an analytical to a more predictive approach, we developed Gaussian Bayesian Networks. The following sections explain the work in more detail.

2.3 Data Collection and Hypothesis Development

The objective of data collection and hypothesis development is to develop analytical capabilities from the plethora of data collected from multiple sensors on the production line. The data is stored on a server where the data are aligned in a relational tabular database

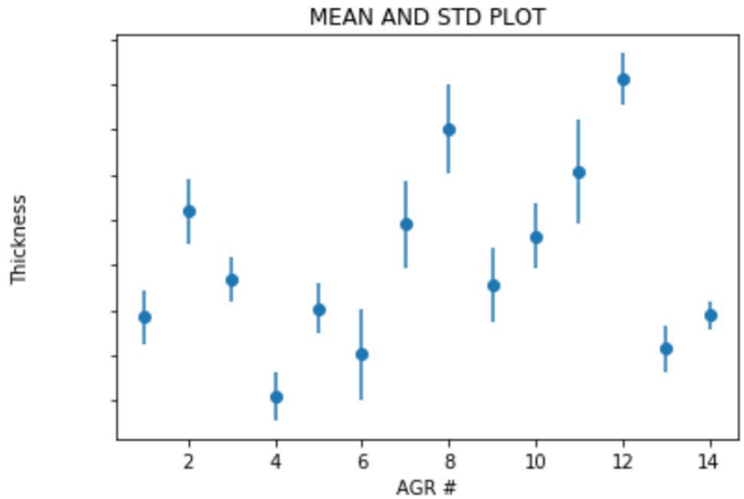


Figure 2.1: Mean and Standard Deviation trend of the collected thickness data

format, and can be easily extracted through queries written in Python or MySQL. One of the major output or dependent variables are the produced container specifications in terms of thickness collected at the end of the process. To start with data exploration, the first task was to look into the statistical measures of the thickness and process data to observe the trend and patterns especially at the sensors used as kickout criteria. The objective of this activity was to make sure the data being collected for multiple containers shows a mean value close to the desired values with low standard deviation (problems especially came as each of the 16 container data collected comes from a different cavity in the blow-mold process). The root cause identification for high standard deviation was the next step either as measurement noise or process noise. Figure 2.1 shows an example trend in the thickness mean and standard deviation measurement values at various locations. As we can clearly see from the plot, those measurements at certain locations like 4 and 6 are too thin, while those at locations 8 and 12 are too thick. The variation at certain locations like 6, 7, 8 were identified as measurement noise due to the placement of those sensors on the measuring equipment, while those at 1, 2, 10, 11 (critical for kick-out) were due to process noise.

As mentioned before, the aim is to identify process variables which are correlated to thickness measurements (both from a data and physical understanding point of view) in order

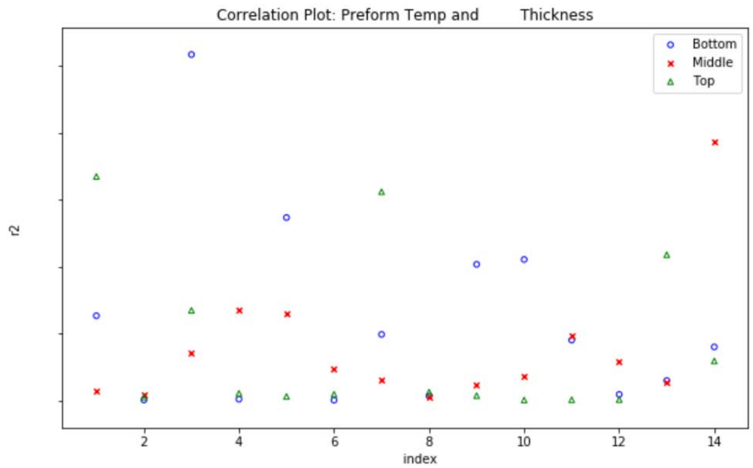


Figure 2.2: Correlation Analysis between Preform Temperature and Thickness

to optimize the process by controlling those variables. An example of correlation analysis between the preform temperature (the temperature of the pre-product before stretch and blow process) at the critical zones (Top, Middle and Bottom) and the thickness at various locations is plotted in Figure 2.2. This graph does not indicate a clear trend due to faulty data but is an example of the approach taken to perform a location and correlation mapping in terms of Pearson's coefficient between the variables. As we can see for location 1 there is high correlation seen with top preform temperature opposed to location 10 having high correlation with bottom preform temperature. This gives us a broader idea that the top preform maps to locations 1-4 on the container, while the bottom preform maps to locations 10-13 on the container. Such a correlation analysis is repeated for various process variables like conditioning, stretch-blow, injection parameters, etc. Each of these correlations either in terms of r^2 or simple 2D plots between the dependent and independent variables helped us develop a causal relationship structure between variables from the start to the end of the process, like in Figure 2.7.

Once we have identified the key process variables affecting the thickness measurements at various sensor locations, whether directly or indirectly, these hypotheses need to be confirmed through various simulations, experiments and statistical testing. We started by making a priority list of some of the key variables (showing high r^2 value), using Aspen

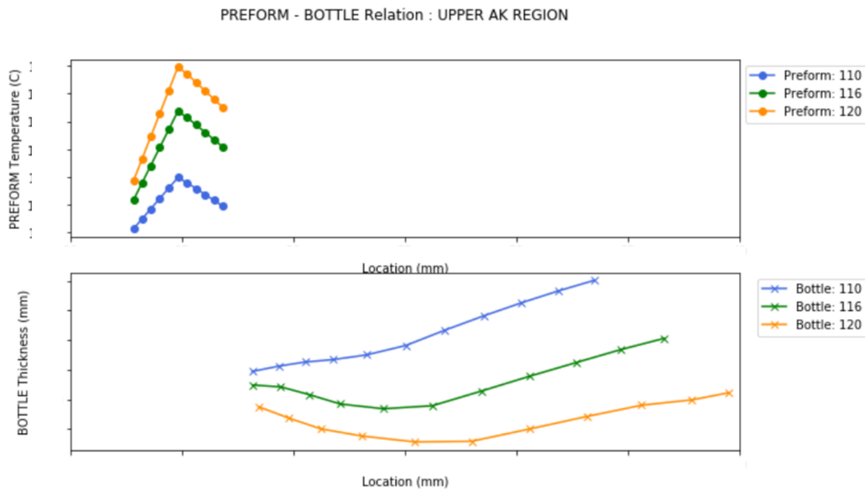


Figure 2.3: Location Mapping Analysis using Ansys Simulation

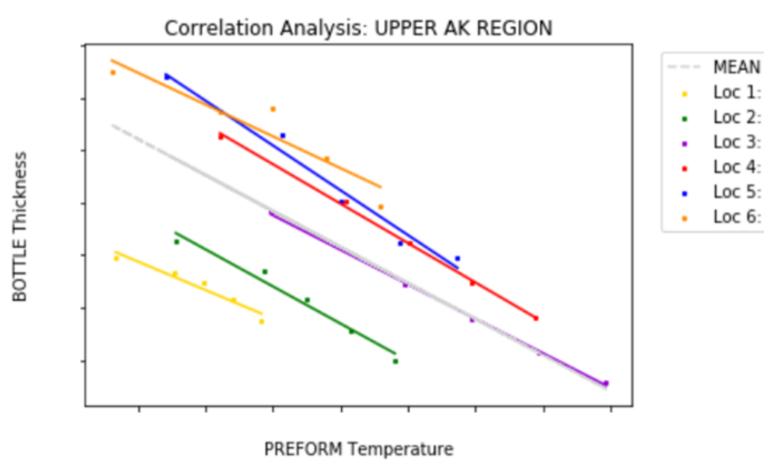


Figure 2.4: Correlation Analysis using Ansys Simulation

simulations to observe the effect of these variables. We also identified a range and step size for each of the variables where they significantly affect the material distribution, which is then used for the next few steps of performing experiments and quantifying this relationship through linear/non-linear equations. Through these simulations, we also performed a theoretical location-mapping to understand where each zone of the preform corresponds to on the formed container. Figure 2.3 indicates the location-mapping from the preform (top plot) to the formed bottle (bottom plot), the trend shift on increasing preform temperature at certain locations shows the material distribution/ expansion once the preform is stretch-blown. Figure 2.4 shows the correlation analysis between preform temperature and bottle thickness measurements at various locations together with the mean fitted line to form a static linear regression model. The results were used for pilot plant studies, where on a single cavity machine each of the process variables was altered between the range identified in simulations. The data were collected for the thickness at various locations. In order to perform location-mapping on a pilot scale, we carried out a UV light ink-jet marking on the preform (physical marking was not possible as this is a continuous process), the location and extension of 'I' or 'T' marked shape indicates the mapping and extent of the expansion or contraction on varying the process variables. The data so-collected was cleaned, analyzed and showed results in accordance with the simulation results (confirmed through a T test, a statistical technique to accept a null hypothesis in this case as the sample size 30). Figure 2.5 shows an example of the results we obtained. This clearly shows the movement in the I shape on increasing the preform temperature, thus enhancing the material distribution. The next step was to confirm these pilot plant studies with the production line where there is an added complexity of process noise (as this is a continuous process). Similar experiments were repeated on a large scale, where the process variables were varied between the range identified and the data so-collected were analyzed to develop correlations and static regression equations which provided an analytical and capability of the process both for optimization and control. Figure 2.6 shows some of the results of these correlation analysis through linear plots and sensitivity analysis as a heat map, it clearly indicated a strong relation between the temperatures and a higher sensitivity of the latter to thickness readings

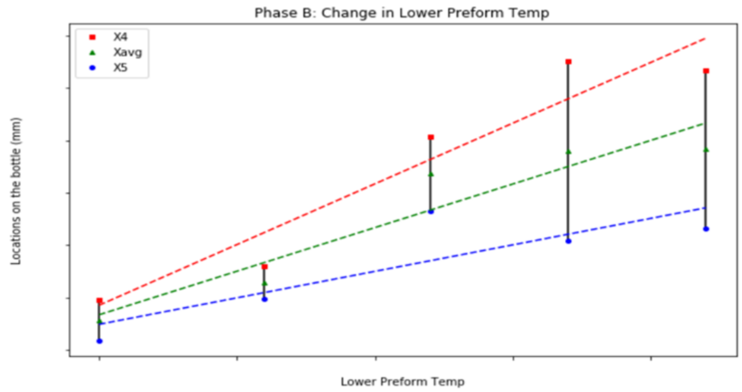


Figure 2.5: Location Mapping Analysis through Pilot Plant studies

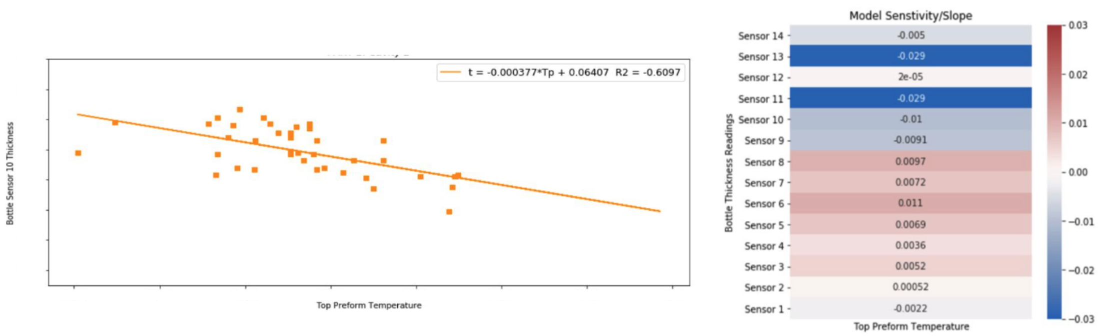


Figure 2.6: Correlation Analysis through Large Scale studies

from the bottom sensors. But the major disadvantage of these static model equations is that they fail miserably even if set points are changed for any process variable, or working with a new product entirely. In such cases, the experiments need to be repeated, which is both time-consuming and expensive. Hence we need a data-driven model which can retrain itself every few weeks, thus automating the process modeling. This is discussed in the next few sections.

2.4 Gaussian Bayesian Networks

As mentioned and derived in the previous sections, the causal relationships between variables can be verified using statistical testing and modeled using first order linear equations. But the caveat in this process is that, for any slight change to the process, such experiments have to be repeated. In order to automate this process, and reduce the labor-intensive process of conducting experiments, collecting data, performing statistical tests and developing linear models which are to be utilized by process engineers to optimize and control the process, we propose a better strategy to utilize the gigabytes of data being collected everyday from the processes. Data-driven approaches for the computational modeling of processes have entered every sector from a simple linear regression between process variables to the use of neural networks for drug development and many more. Most of these algorithms have two approaches, either a deterministic route to develop model equations to get the point estimates, or a probabilistic route to obtain these relationships as probability distributions which provide point estimates along with a confidence interval. A number of these algorithms take the probabilistic route, like Bayesian Networks (BN). Bayesian Networks are Directed Acyclic Graphs (DAG) structures created to model a complex process with multiple conditional dependencies between variables; an example is shown in Figure 2.7. Here one can clearly see the complex, but conditional, dependence between various variables like x6 and x4 have a direct correlation. But x8 and x4 have a conditional indirect relationship. Such structures can be used for various cases, not just for prediction. For example, Friedman, Linial, Nachman, and Pe'er (2000) used Bayesian Networks to understand the mechanism and the causal relationships between different expression levels of various genes. While Lazkano, Sierra, Astigarraga, and Martinez-Otzeta (2007) used such an algorithm for mobile robots for door-closing tasks using sonar readings. Such Probabilistic Graphical Models (PGMs) do provide some advantages over Generalized Linear Models (GLMs: Linear and Logistic Regression) and Neural Networks (NNs: deep learning approaches) since they follow the so-called "white-box" approach. A physical understanding of the processes are best captured using this technique. PGMs act as an extension to GLMs as they model the relationships between variables which are considered as independent features in the latter. Due to such relationships, they can be better understood compared to NNs, especially by those with little or no knowledge of AI or machine learning.

Using Bayesian Learning one can easily model the conditional posterior probabilities through

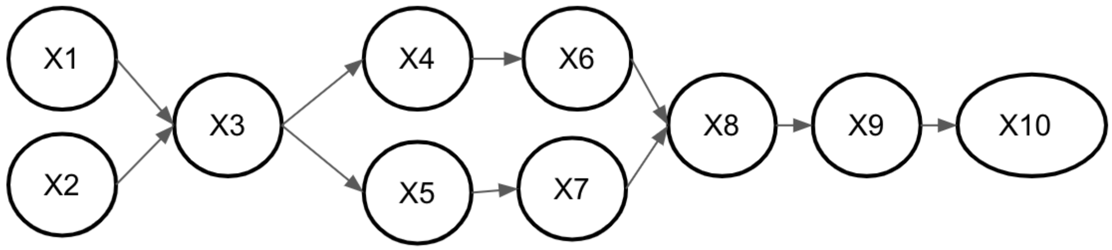


Figure 2.7: Bayesian Network: Directed Acyclic Graph of 10 nodes

the well-known Bayes Theorem, as listed in Equation 1. Some of the advantages of going this route are, first, the parametric model is estimated as a likelihood function for a given variable and data and second it gets updated with more evidence i.e more data being collected. Based on a physical understanding of the process we can make an assumption of the prior like in this case the Gaussian distribution (most process variables are normally distributed) or start with no assumption like a Uniform distribution. Each of the edges in the Bayesian network structure are formed as parent-child relationships and can be drawn from the various hypothesis and results carried out in Section 2.3, and are modeled as conditional or joint probability distribution for each parent-child edge, while the entire network is modeled as a joint probability distribution expressed as the product of all conditional probability distributions as shown in Equation 2.

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)} \tag{1}$$

$$P(X_1, X_2 ... X_n) = \prod_{i=1}^{n} P(i|Par(i)) \tag{2}$$

Here, the relationships between process variables are modeled as a Bayesian Network structure connected through conditional probability distributions. Different variables like source and product temperatures were related through a conditional probability distribution. And from the results of the analysis of various hypothesis experiments conducted in Section 2.3, we can conclude that each of these probability distributions is a **Linear Gaussian**

Distribution. The expansion of probabilities in Equation 1 are listed in Equations 3 to 4. Additionally, the multivariate joint probability distribution in Equation 2 can be expressed in terms of mean and co-variance matrix using a simple Gaussian expansion listed in Equation 5, where p is the number of samples in the data-set. We can clearly observe from these equations that the point estimates/expected values of the Gaussian distribution represent a simple linear regression model quite similar to the static model derived in the previous sections. But the added advantage of this technique is it uses the plethora of data to fit probability distributions according to the parent-child relationships as described in the Bayesian Network structure, and uses the fitted model to provide both the expected values and the 90-95% confidence interval based on the variation requirements. The parametric model parameters can be easily derived through various mathematical techniques like linear algebra, discussed more in the next section.

$$Par(Y) = X = [X_1, X_2, X_3, ..., X_m] \tag{3}$$

$$P(Y|X) = N(\beta_1 X + \beta_0, \sigma^2) \tag{4}$$

$$P(X_1, X_2.., X_n) = \frac{1}{(2\pi)^{p/2}(\Sigma)^p} exp(-\frac{X_{diff}\Sigma^{-1}X_{diff}^T}{2}) \tag{5}$$

2.5 Model-Building

In our case we wanted to utilize the data from the sensors to build models in an automated fashion. Once, the key variables in the process are identified like we did in Section 2.3 for the entire process, the Bayesian Network is formed to define the parent-child relationships as shown in Figure 2.7. After having the structure and architecture in place along with a good flow of data from each process variable or node, the next step is to formulate the conditional probabilities by deriving the coefficients namely β_1 and β_0 for each of the conditional probability distributions in Equation 4 from the μ and Σ matrices in Equation 5. The cost function for such kind of model goes into minimizing the error between μ and Σ matrices found iteratively through sampling the data-set with repetition. The coefficients

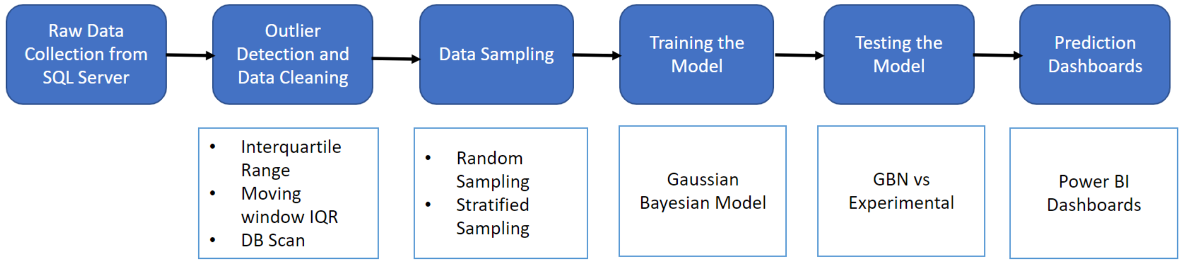


Figure 2.8: Model Build Process Flow for Gaussian Bayesian Networks

are then formed from a part of these matrices as described in Equations 6, 7, 8, and 9.

$$P(X,Y) = N(\begin{pmatrix} \mu_X \\ \mu_Y \end{pmatrix} \begin{pmatrix} \Sigma_{XX} & \Sigma_{XY} \\ \Sigma_{YX} & \Sigma_{YY} \end{pmatrix}) \tag{6}$$

$$\beta_0 = \mu_Y - \Sigma_{YX}\Sigma_{XX}^{-1}\mu_X \tag{7}$$

$$\beta_1 = \Sigma_{XX}^{-1}\Sigma_{YX} \tag{8}$$

$$\sigma^2 = \Sigma_{YY} - \Sigma_{YX}\Sigma_{XX}^{-1}\Sigma_{XY} \tag{9}$$

The values of the parameters of the model namely β_1 and β_0 holds true when we have sufficient and good data to capture all possible scenarios of the process. There are a number of data collection and preprocessing steps that need to be carried out before we can use it to develop a parametric model. Figure 2.8 describes the entire process flow that went into building this model from scratch from data preprocessing to post processing of the parameters as dashboards available to the process engineers on the line. In our case the data coming from sensor variables i.e from the server was of sufficient amount but there were some variables like moisture content of the PET resin before they are injection molded that needed to be estimated. We know that the drying process of the resin is a mass transfer process so we tried to model the moisture content from "Fick's Second Law of Diffusion" and the procedure is laid out in Figure 2.9. We simplified the model to get a simple exponential equation dependent on initial moisture content (fixed by the manufacturer) and the dwell time (retrieved from sensor data). The values so retrieved from this equation were very

Ficks 2nd Law: The rate of accumulation is directly proportional to concentration gradient

$$\frac{\partial(\rho_s X)}{\partial t} = \nabla(D\rho_s \nabla X) \tag{1}$$

$$\frac{\partial X}{\partial t} = D\nabla^2 X \tag{2}$$

$$\frac{\partial X}{\partial t} = D\nabla^2 X - K_m(X - X_{air}) \tag{3}$$

$$\frac{\partial X}{\partial t} = -K_m(X - X_{air}) \tag{4}$$

$$\frac{dX}{dt} = -K_m(X - X_{air}) \tag{5}$$

$$ln(\frac{X - X_{air}}{X_0 - X_{air}}) = -K_m(t - t0) = -K_m \Delta t \tag{6}$$

$$X = X_0 e^{-K_m \Delta t} \tag{7}$$

Figure 2.9: Moisture Content Estimation Procedure

close to experimentally determined values of moisture content, it was then preprocessed and fed to the model to develop the Gaussian Bayesian Network.

After data for all the variables in Bayesian Network Structure is retrieved, the next step is to clean the data of any outliers but to make sure we have enough range in the data to make high confidence estimates. We tried various outlier detection algorithms to clean the data-set, they varied in their technique and the variable they were applied to. One of the novel approaches we used was a "Rolling Window Inter Quartile Range Filter". As the distribution of the data is assumed to be Normal/Gaussian, a outlier is defined as point which is outside the $1.5 * IQR$ window. This is a standard IQR approach for outliers, but here we make IQR as a moving window filter as the set-points of variables are continuously varying thus having a fixed value can result in a number of false positives/negatives. Figure 2.10 shows this approach using an example data set and the predicted outliers are indicated as false positives/negatives in the second sub-plot. As we can observe that using this approach the number of FP/FN are kept to a minimum even with the change in the set-point of the variable which might not be fully captured by a standard IQR approach.

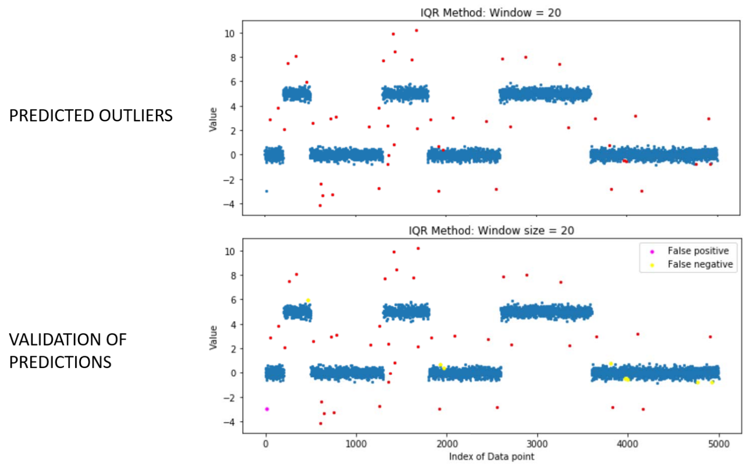


Figure 2.10: Outlier Detection Model Results

Once we have a clean data-set the next step is to start training the model. As mentioned earlier, equations 7, 8, and 9 are used to develop initial estimates of the model which is then trained iteratively to minimize the loss in μ and Σ matrices using the loss function as mean squared error. Once trained this modeled is tested against a new data-set to make sure the model is not under/over fitting. Another comparison was also done with the static experimental models derived in the data collection and hypothesis development section. Figure 2.11 clearly indicates the similarity of the two models. The requirement of these models was to implement them in real-time, we needed to reduce the computational time thus by reducing the amount of data fed to training the model we avoiding the complication of over-fitting. This selection of a sub-data-set for training was done using data sampling. We tried 2 approaches namely random and stratified sampling, latter performed better due to the formation of multiple strata for different set-points.

Lastly this model today is deployed on-line as prediction dashboards hosted on the cloud server. These models are regularly updated based on the feedback from process engineers and stakeholders and is proving to be a great tool in optimizing and controlling the process parameters for a better and more efficient production of high-quality plastic containers.

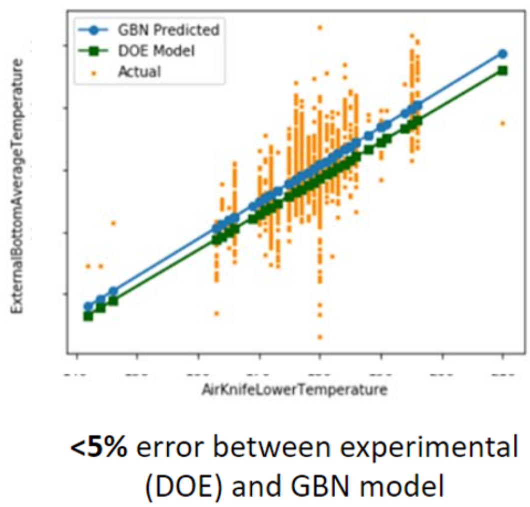


Figure 2.11: Comparison of Experimental and Data Driven Model

2.6 Extension to Root Cause Analysis

Our next aim to enhance the predictive capabilities of the process, not only for process optimization and control, is to build fault detection and root cause analysis algorithm. Imagine if a fault occurs in the process. First, we need to detect it from the data using the joint probability distribution we estimated in the previous section. We also need to identify the root cause and the pathway using the Bayesian network structure and the "parent-child" relationships, as shown in Figure 2.7. The work for this algorithm is in process and has not been finalized yet.

Chapter 3

Inline Quality Control using Computer Vision Tools

3.1 Introduction

In order to meet the increasing demand, most manufacturing sectors have developed processes with high yields using state of the art technology, as described in the previous chapter. But product consistency also has to be maintained; this requires a more efficient process and faster quality control (QC). QC is one of the vital parts of the process, especially for a multi-stage production system. Often, QC is done manually on the line by picking up random samples and performing certain listed tests on the products. More traditional techniques include the use of Statistical Quality Control Charts on the line, as shown in Godina, Matias, Azevedo, et al. (2016). Decisions regarding the quality of the manufactured products are made using various plots of the statistical measures, like x-bar and standard deviation. In the age of digitization to reduce human effort, several new techniques have been proposed. For example, Rocha, Peres, Barata, Barbosa, and Leitão (2018) propose an automated ML model to construct decision-rules regarding the quality of the product with minimum human intervention. This chapter describes another interesting approach towards this goal: Inline quality control of the product specifically to identify a good vs. bad product, based on residual stress profiles using a state of the art computer vision technique named “convolution neural networks.” Each section in here describes the theory and the methodology followed for this project.

3.2 Photo-Elasticity Measurements

PET containers are polymer-based products exhibiting residual stresses due to the injection molding process by which they are formed. These residual stress patterns can be used to identify the strength of the product, especially to estimate the probability of the resultant blow-molded bottle being defective. A common technique is to observe residual stress patterns, i.e., the stress remaining in the material after external forces are applied. In this case, the injection molding represents the external force. To maintain mechanical equilibrium in the product such residual stresses can be generated; these can be used to classify the product as good or defective. But these residual stress patterns are not visible with the naked eye, and require an optical technique to view these trends. A well-known technique, "birefringence" or "photo-elasticity," can quantify the optical quality of the substance in the form of an image (Aben, Ainola, and Anton (2000)).In this method, the stress fields are visible when a monochromatic light is passed through a material (photosensitive containing the residual stresses). This resolves the light into two components with different refractive indices (hence the name double/bi-refraction). The difference in the refractive indices creates a phase difference between the two components, which then creates a fringe pattern which can be correctly captured through a camera/sensor. The equations listed below are an optics law (Equation 10) and fringe equations (Equation 11) that correctly quantify such phenomena in terms of phase retardation and the number of fringes in the pattern (Noyan and Cohen (2013)). It can be observed from these equations that N and Δ are dependent on t, the thickness of the photosensitive material. It is observed in our case that a good pre-product within the desired specification range produces a uniform residual stress birefringence pattern. In contracts, a defective one produces different kinds of random patterns, dependent on how much the thickness varies from the desired specifications.

$$\Delta = \frac{2\pi t}{\lambda} C(\sigma_1 - \sigma_2) \tag{10}$$

$$N = \frac{\Delta}{2\pi} \tag{11}$$

3.3 Experimental Setup

The objective of the photo-elasticity experiments was to create a data-set for all residual stress profile images of the products, which will be further input fed to a computer vision algorithm for classification. In this data-set there are changes in the residual stress profile pattern as we shift from good (uniform) to a defective product (disoriented). In order to get the data-set for such residual pattern images, 350 good and defective products were collected from the production line. Each of the collected products was placed on a customized holder and photo-elastic measurement technique, as described in the above section was used to visualize the residual stress pattern. The holder with the product was placed between the light source and camera with the polarizer film to generate a monochromatic light from the white light source, as shown in Figure 3.1. The received image were the residual patterns and the process was repeated for all the collected products, good or bad. The obtained image data set was then pre-processed and fed to the classification algorithm for in-line quality control.

3.4 Convolution Neural Networks

As for the classification task to identify the product good or defective from residual stress patterns, we use a state of the art computer vision technique in deep learning known as "Convolution Neural Networks" (CNN). CNNs are advanced neural networks to handle 2D/3D, more specifically image data. The concept of neural networks was inspired from biology, specifically the nervous system (connection of neurons) in our body, in which each of the neurons perform a simple task of passing the messages, but the network overall can

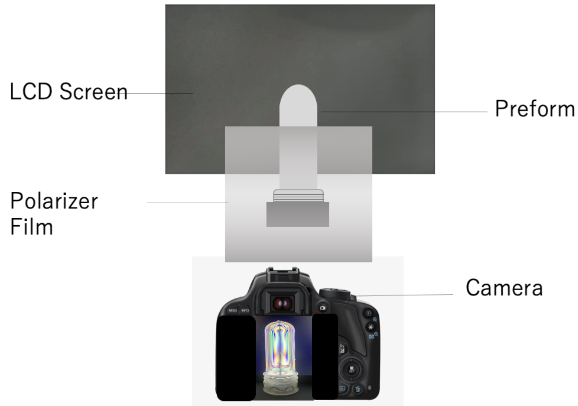


Figure 3.1: Experimental Setup for Photo-elasticity measurement for visualizing residual stress patterns

perform complex and multiple tasks like running, reflex actions, etc. Similarly, a "Perceptron" or a single-layered neural network, utilizes the combinatory power of individual neurons performing simple functions, like the evaluation of a non-linear function over a linear combination of input features (Figure 3.2). CNNs are an extension to neural networks where, in instead of multiple neurons for an initial few layers in the network, there is a kernel of a certain size which performs the convolutional operation over the input image (a 2D/3D matrix of pixel intensity values). This convolutional operation can be compared to a "moving dot product" operation between matrices. This is a repetitive operation between the kernel matrix and a part of the image matrix of the same size as the kernel, which results in another matrix of a different size. CNNs are preferred over Neural Networks as they involve fewer parameters to learn/fit the model. This is especially helpful when the input feature size is huge (each pixel can be considered as a feature). This approach makes the model training process faster, especially for large images. A simple convolution neural network for a binary classification task is depicted in Figure 3.3. O'Shea and Nash (2015) tdiscuss how the number of parameters that have to be learnt increases exponentially for a NN when training over image data, especially with RGB (red/green/blue) images. Thus, a CNN approach has a great advantage over a NN since, irrespective of the image size, the kernel size for the convolution operation over the image data set remains constant with increase in the image size, thus limiting the number of weights that need to be learnt.

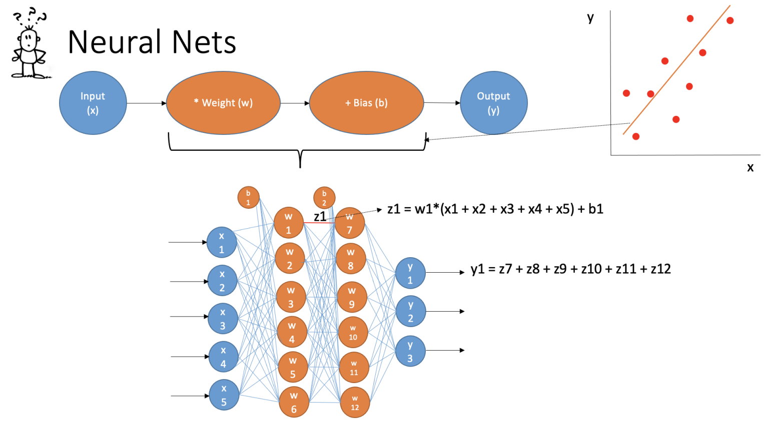


Figure 3.2: A Simple 2 Layer Neural Network Explanation

As CNNs are inspired by NNs, their training, i.e., the forward and backward propagation, is very similar to that of a neural network. The weights and biases in a neural network are the parameters of the model which have to be learnt through the data used for training such a model. The learning aspects of these networks happen during the backward propagation where the objective is to find the optimal choice of weights and bias for each neuron in each layer which minimizes the cost function (the sum of errors between the actual and predicted values). Every image/ data point fed to such network structures moves the weights and bias towards the optimal value one step at a time using an iterative approach commonly known as “gradient descent”. While building the model for a specific application, the architecture, the loss function, optimizer algorithm, and non-linearity component have to be tuned in order to minimize the error. The next section describes the model build, data preprocessing, hyperparameter tuning and evaluation techniques we used for our CNN model to perform the classification task on the image data set collected from the photo-elasticity experiments.

3.5 Model Building

The initial CNN Model Architecture was inspired by a simple “dog-cat” image classifier, well-known in the deep learning sector. But before getting into the model architecture and

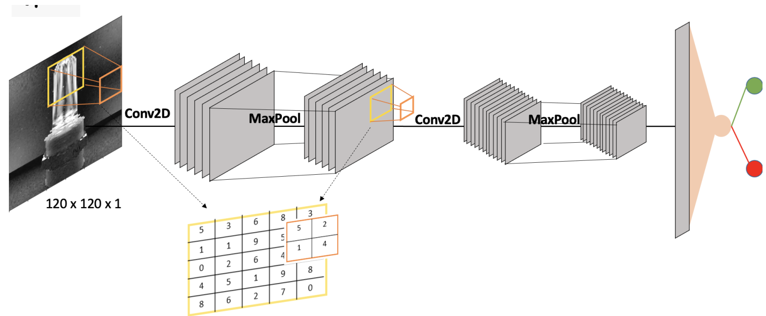


Figure 3.3: Convolution Neural Network Model for Binary Classification

training, the image data-set needed to be preprocessed to avoid under- or ove-r fitting of the model (one of the most common problems in machine learning). The requirement from the model is that it should perform well on the data fed to it (to avoid under-fitting), but be generalized enough to still perform well on new input data (to avoid over-fitting). There were 700 images collected (good and bad) through the experiments conducted in Section 3.3. We use this data for three tasks: training the model to learn the weights and biases, validate the model for hyper-parameter tuning (like architecture, loss, optimizer, etc.), and, lastly, test the model on a new data-set. As the image data-set was limited, the validation data-set for hyper-parameter tuning and test data-set for testing the model was restricted to 200 images combined. In the training data-set, there were 225 good and 225 bad images. Each of these images was binary-labeled (0 for good and 1 for bad), resized to a shape of 120*120 (height x width) (found as the optimum size, neither under- nor over- fitted) and gray-scaled to reduce the complexity of multiple color channels.

The CNN model architecture was finalized to have Convolution and Max-Pool (size reduction) Layers with a kernel size of 3*3, in order to create a feature map. This is a grid map of the input image containing all the characteristic features, which can very well classify the product, for the photo-elastic images. These stacked-up layers were followed by a flattening layer to convert from 2D to 1D input vectors. Further followed by the fully connected layer before final output layer to extract essential components as a single vector from this feature map in order classify the images. In the output layer, using a sigmoid

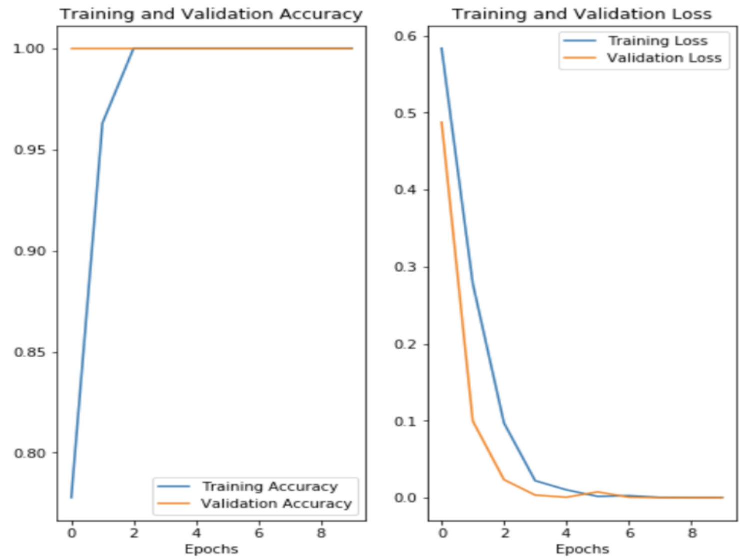


Figure 3.4: Training and Validation Loss and Accuracy curves

as the activation function (the non linear function the neuron applied on the linear combination of the input features), we obtain a single value indicating the probability for the product to be defective. As probability values lie in the range of 0 and 1, we chose 0.5 as the threshold. Values above this would be classified as defective or labeled as 1. The model was trained using the preprocessed training data-set and, as mentioned in the previous section, the weights were learnt using backward propagation., Here the loss function was set as the binary cross entropy loss described in Equation 12, commonly used for such binary classification tasks. The hyper-parameters included the kernel size, number of nodes in the fully connected layer, the optimizer algorithm, number of iterations for the gradient descent algorithm, etc. These hyper-parameters were tuned by observing the validation and training losses, as shown in Figure 3.5. Finally, the model was tested using the test data-set and the results are described in the next section.

$$L = \sum_{i=1}^{n} (y_i log(h(x_i)) + (1 - y_i) log(1 - h(x_i))) \tag{12}$$

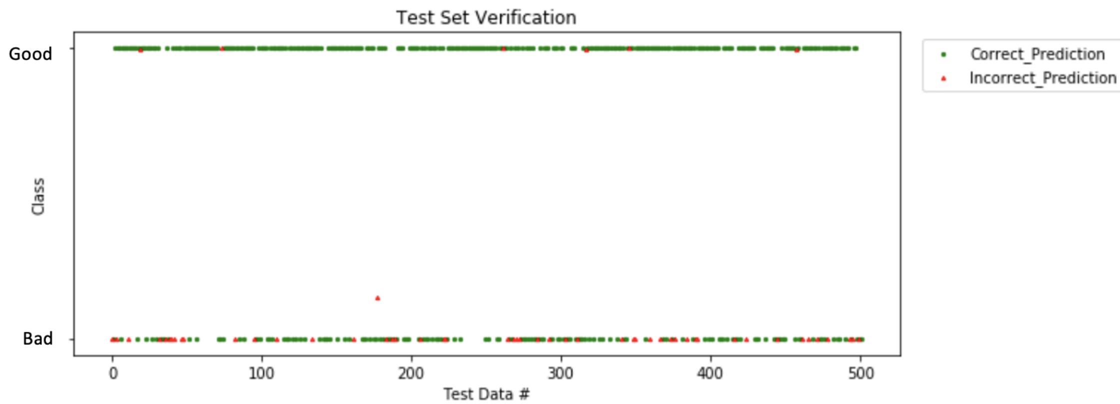


Figure 3.5: CNN model performance on Test Data-set

3.6 Results

We can observe from Figure 3.4 that the training and validation curves almost converge to maximum accuracy and minimum loss. This is an indication that the hyper-parameters are well-tuned and the model does not suffer from any under- or over-fitting problems. In order to test the model on an entirely new data-set entirely, we generated and preprocessed as mentioned in the previous section a set of 100 images. This model showed an accuracy of 88.85% and an F1-score of 0.91 (formulas listed in Equations 13 and 14) for the classification task between good and defective product images from the photo-elastic measurements. Figure 3.5 shows the classification performance of the model on the test data set. This whole methodology for in-line quality control was recently **accepted for a patent in the name of the firm**.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{13}$$

$$F1Score = \frac{TP}{TP + 0.5 * (FP + FN)} \tag{14}$$

Such a technique constituted a proof-of-concept project for the in-line quality control possible through computer vision tools like CNNs. This approach could replace manual Inspection on the line which may involve human error factor. With the advent of AI and Machine

Learning, a number of firms are moving towards automating the process of visual inspection and making the process more robust by decreasing the number of false positives/negatives using such techniques. With the increase in demand of the products, manufacturing firms are trying their best to fasten the production as well as quality control process, there is an urgent need for such tools as manual inspection is physically impossible if the line runs at a high speeds and produces a large quantity of products. Industries like automotive and semiconductor have already adapted such tools as part of Industry 4.0, and increasing number of firms are realizing the importance to use such data driven tools to automate and improve their processes.

Chapter 4

Predictive Maintenance using Machine Learning

4.1 Introduction

In most industries, maintenance is one of the biggest reasons to shut down a production line. This plays a considerable role in lost production. Randomly occurring failures are hard to locate and time-consuming to resolve, this is the Run to Failure (R2F) strategy. To avoid this, often plants follow a Preventive Maintenance (PvM) strategy where a maintenance procedure for all equipments is scheduled every other week or fortnight based on the equipment. This has an added advantage over R2F as this ensures that each equipment is performing as desired. Often this leads to additional maintenance, even when not required, as the time interval between procedures is hard to estimate. In some cases, it incurs additional costs over R2F. especially for expensive and complex machines which have a time-consuming and costly maintenance procedure.

AAnother approach is Predictive Maintenance (Pdm) in which the strategy is to use sensor data to predict failure occurrence and schedule maintenance procedures accordingly. This is based on Remaining Useful Life (RUL) predictions, i.e., the time left before the equipment fails. Such a strategy minimizes maintenance costs and production losses, as well as maximizing equipment life. There are multiple ways to pursue PdM as a part of

Industry 4.0 and one of the methods which is being adopted rapidly by various industries (as mentioned in Chapter 1) is a data-driven strategy. There are many possible algorithms; the choice and parameter-tuning of such tools are problem/ situation-specific. With such a data-integrative approach, machine downtime can be reduced, making it easier to find the root cause, with cost-savings and reduced as well as increasing the efficiency of the equipment (Carvalho et al. (2019)).

There are two approaches to an ML-driven PdM that include supervised and unsupervised learning. The former requires a large historical labeled data-set, with different cases of failures on the machines. This is similar to the approach seen in Chapter 3, trends/patterns in sensor data can be identified to predict the remaining useful life, helping to determine when failure is likely to occur. The latter approach tries to find trends in the data without historical knowledge of the failures. Either of the two approaches can be chosen based on a number of factors, like the availability of historical data, a trade-off between efficiency and accuracy, etc. There are a number of algorithms to tackle this, each with its own pros and cons (Paolanti et al. (2018)).

The problem statement provided to us was to develop a PdM strategy for the process modeled in Chapter 2. We started by analyzing the downtime and maintenance cost per equipment (manually) in the process for the production of high efficiency plastic containers. We also met with operators and process engineers to understand their view point based on years of experience supervising the machine. The two major bottlenecks we uncovered involved mechanical and thermal equipment; both of which had long down-times and high occurrence. The PdM approach for such equipment included analyzing the vibrational signals from the equipment (mechanical) or temperature and pressure sensor data (thermal equipment). This was followed by developing models to predict failures in each case, hence developing a predictive capability for scheduling maintenance procedures. Section 4.2 describes supervised approach in detail with proof of concept examples. Section 4.3 describes an unsupervised approach often used in natural language processing problems. Using the human-recorded maintenance dispatch history data on the line, our goal was to identify the root cause component, which had the highest occurrence, and large downtime during the preceding 6-12 months. . This chapter describes several approaches to utilize machine learning in predictive maintenance and root cause identification as a PdM strategy for a given process.

4.2 Predictive Maintenance using Sensor Data

In this section, predictive maintenance is carried out through condition-based maintenance. Hashemian (2010) explains different state-of the art approaches to develop a PdM strategy for sensor data from mechanical components, like vibrational amplitude signals, or thermal components, like thermocouple and pressure data. The three projects used a correlation analysis between variables as well as feature identification for a complete condition monitoring of the equipment. Kaiser and Gebraeel (2009) depict the latter approach in a different way by utilizing the sensor variable degradation patterns to provide a better estimate of remaining useful life of the equipment in a more real-time fashion by a feedback loop technique. Depending on this estimate, the proposed algorithm also provides a better suggestion for scheduled maintenance compared to conventional techniques. Inspired by these strategies, we propose similar PdM strategies for our problem statement.

As mentioned in the previous section, the two bottlenecks identified involved mechanical and thermal equipment. Predictive maintenance for these two cases was carried out as separate tasks, first fault diagnosis using the vibrational signals on mechanical equipment and using sensor data for predictions of Remaining Useful Life. Both these examples were carried out as proof of concept projects using small data-sets which are then implemented for larger-scale scenarios in the plant.

4.2.1 Approach 1: Fault Diagnostics

For mechanical equipment, one of the major tasks is to identify if a fault has occurred at an early enough stage, before it undergoes permanent damage. Here, we have a time-dependent vibrational signal from the equipment. Our proposed strategy for fault diagnostics is to identify these faults by analyzing data in a different domain than time. So the first step is to convert the data from a time to a frequency domain using Fast Fourier Transform. Figure 4.1 shows the transformation both for normal and faulty signals. Fast Fourier Transform (FFT) of this data makes the identification of faults easier through peak identification. FFT algorithms are quite well known especially in computational simulations or signal processing to perform discrete Fourier transforms or inverse discrete Fourier transforms at a faster rate by reducing the complexity of algorithms from $O(N^2)$ to $O(Nlog(N))$ (Cochran et al. (1967)). Our approach includes converting signals from a time domain to a frequency domain and then performing peak identification using a classification machine learning algorithm. As indicated before, this is a "supervised" approach, which requires significant historically labeled data. This algorithm, once trained, is fed frequency domain data continuously, or in real-time, and can detect whether the machine state is 'normal' or 'abnormal.' It used fault identification/labeling to determine specific concerns, e.g., a bearing issue, or mechanical loosening, etc. we could not model this scenario due to lack of an historically labeled data-set. But such an approach for vibrational signal analysis is simple and has immense potential to show good accuracy in real-time classification/ fault diagnostics.

4.2.2 Approach 2: Remaining Useful Life Prediction

For thermal equipment, we have sensor-based data arising from variables such as temperature, pressure, speed, etc. The objective is not only to correctly estimate the fault by looking at sensor degradation patterns, but also to provide a good estimate of remaining useful life. Here, we start with labeled data-sets with different failure scenarios and hence different cases of remaining useful life for the equipment. The objective is achieved by

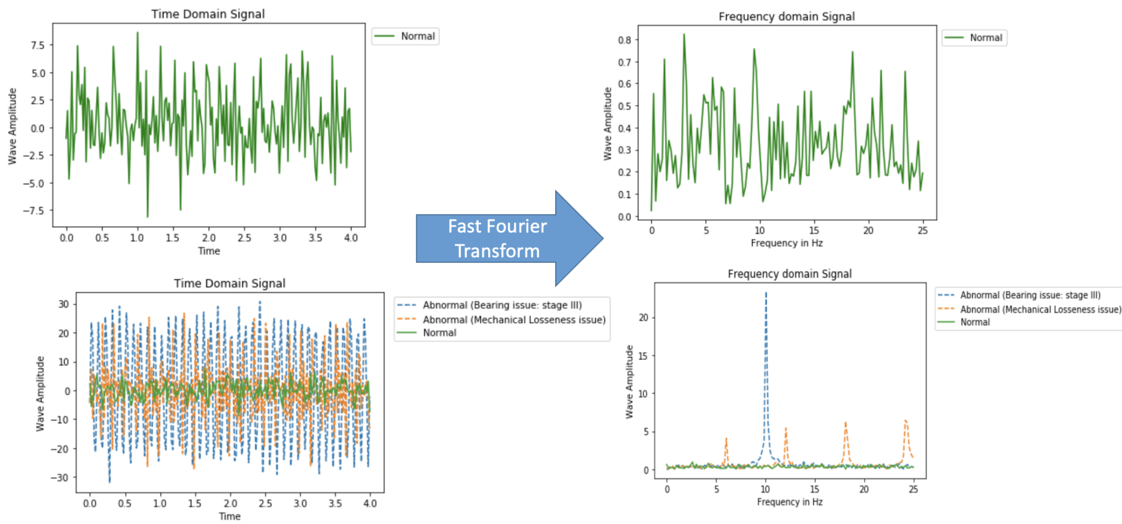


Figure 4.1: Fast Fourier Transform for Normal and Faulty signals from Motor

modeling a regression curve for RUL estimation from patterns in sensor data. To apply a proof-of-concept project to real life cases on the line, we used the NASA Turbojet Engine Data-set, which is open-source. This data-set consists of three scenarios for failure (operational conditions), data from 21 sensors (each scenario having a different trend/pattern of these data-sets), and 100 similar situations for each scenario for RUL prediction. In our process, we also obtain sensor data from 130 process variables in different failure scenarios. Remaining Useful Life prediction is an important part of Predictive Maintenance as this curve can correctly estimate the failure occurrence hence can schedule a maintenance accordingly. As mentioned in the Introduction section, this ensures lower maintenance cost, reduced downtime and higher maintenance efficiency.

Our approach was simply to first perform feature reduction by performing correlation analysis between variables and removing variables with high correlation. As we are dealing with a high number of variables, it is necessary to perform exploratory data analysis first to make sure that the variables used for the final regression equation are independent and identically distributed. This is one of the common assumptions in most statistical and machine learning procedures. Figure 4.2 shows the results of correlation analysis as a heat map. This is a common visual technique to look at the correlation matrix and is easy to

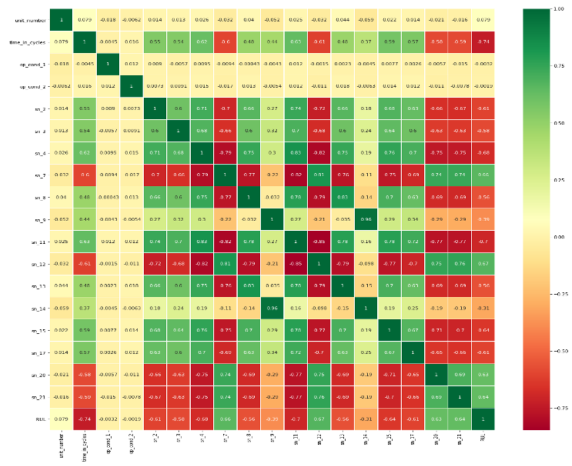


Figure 4.2: Correlation Matrix Heat-Map between sensor variable for the Turbojet Engine

interpret. There are some variables which are highly negatively correlated (the second last two rows/columns), thus a linear combination or one of them can be used in the list of final model features. Even after this initial analysis, the number of variables remains large (20+ features) for a simple polynomial regression curve. Thus, we use Principal Component Analysis to reduce the number of variables to its principal components (namely PC1 showing 75% variance) representing linear combinations of variables. This is a common dimensionality reduction technique in statistics and machine learning. It works on the principle of deriving the principal components as eigenvectors and eigenvalues, common linear algebraic methods. The variance percentage of each principal component indicates how well that PC can explain or quantify the variance in the data as a linear combination of features. There are other techniques for dimensionality reduction but this is often a better starting point one that is well understood and established. The derived principal components (chosen just the first to show the concept) are then related to the RUL from the labeled data-set by curve fitting. In this case, we use an exponential curve fit, as seen in Figure 4.3). The found equation can then be used to predict RUL based on the value of PC1 from the sensor data received Other PC components may provide a better estimation. Figure 4.3shows the PCA/curve fitting studies performed with this data-set. This clearly indicates how utilizing data from sensors interpreted as principal components can fit the noise data for RUL well, hence enhancing the predictive maintenance power on the line.

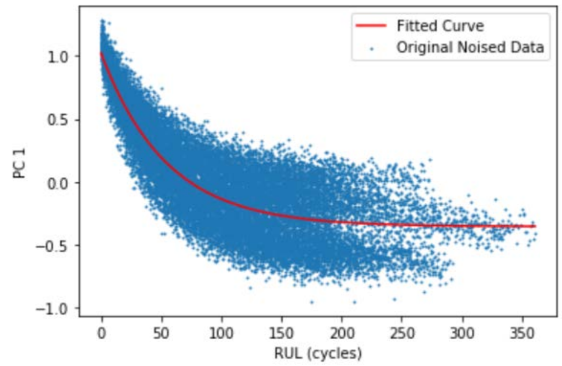
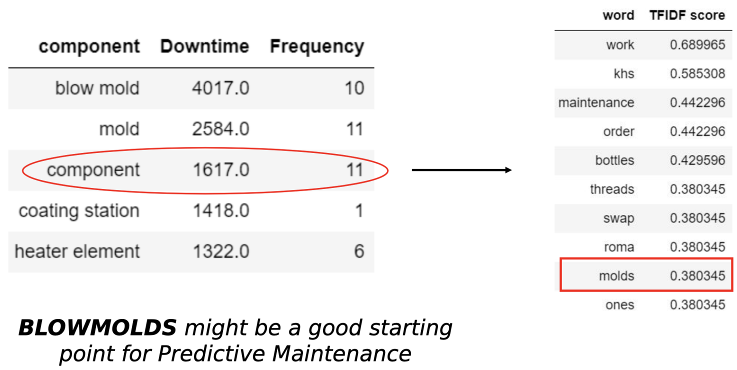


Figure 4.3: Curve Fitting between the Principle Component and RUL

4.3 Predictive Maintenance using Human Recorded Data

This work was carried out as an exploratory project to utilize human recorded data ,in this case maintenance records (maintenance dispatch histories) on the line. The objective of the activity was to find which component fails frequently. The data-set came from software used on the line to record the maintenance history as "dispatches." This data-set consists of several columns ranging from the ID, the person responsible or tackling the maintenance requirement/fault, comments about the fault, downtime, actions taken to resolve the issue, etc. The fault can be easily identified if a person goes through the excel sheet and reads the comments about the fault. But to automate such a process, we require a more aggressive approach. Such kind of textual analysis techniques are quite common in natural language processing (NLP) problems and often used in web-scrapping projects. Our approach was to use the downtime and the comments about the fault along with this technique to develop a meaningful insight about a component which fails frequently and results in a significant downtime.

There is a technique in NLP for textual data vectorization called "TFIDF": Term Frequency Inverse Document Frequency. All machine learning models accept data in a numeric format, hence it is critical to convert text data into float or integer format. Often the frequency of words in a sentence is a good approach for this task. One of the simplest techniques is a "Count Vectorizer" which is a Boolean conversion. It is '1' if a word is



component	Downtime	Frequency
blow mold	4017.0	10
mold	2584.0	11
component	1617.0	11
coating station	1418.0	1
heater element	1322.0	6

word	TFIDF score
work	0.689965
khs	0.585308
maintenance	0.442296
order	0.442296
bottles	0.429596
threads	0.380345
swap	0.380345
roma	0.380345
molds	0.380345
ones	0.380345

Figure 4.4: TFIDF Score calculation on Human Recorded Data for PdM

present in the sentence, else '0'. This limits the range of the data and takes a lot of memory space to store such frequencies. TFIDF approach vectorizes the textual data by calculating the TFIDF score using Equation 15 and 16, where t, d, n are the term, document, and number of documents, respectively. Such a TFIDF score was calculated for various "words" in the document (meaning comments from the maintenance records). This follows cleaning the data-set from "stop words" in English like "a, an , the, and, between", etc. Figure 4.4 clearly shows an example of the scores and the major component identified for predictive maintenance. The component identified by a simple frequency count identified the faulty component under a general category called "component" which was better analyzed through comments and the TFIDF scores. This approach identified the molds as the troublesome component. This was also confirmed by process engineers on the line which have years of experience with the machine. A plan was proposed to apply the Pdm strategy proposed in Section 4.2.2 to utilize all the sensor variable data coming from "molds" to provide a good estimate of the remaining useful life as well as develop a scheduled maintenance accordingly.

PdM on this component was not carried out due to a lack of data, resources and time. But the results in this chapter shows the considerable potential in this sector for its application, a plan to follow to approach the required goal as well as proof that such techniques work and can lead to minimized maintenance costs and reduced downtime on the line.

$$TFIDF = TF(t,d) * IDF(t,d,n) \tag{15}$$

$$IDF(t, d, n) = log(\frac{1 + n}{1 + DF(d, t)}) + 1 \tag{16}$$

Chapter 5

Summary and Future Work

5.1 Summary

Time consuming manual tasks like approving orders, optimizing a manufacturing process for better production, updating documents, etc. are getting more difficult. In recent years, the world is moving towards automated processes like a database for organizing data as a structured collection, scheduling procedures and meetings, or just running a simple program to add 2 numbers. As mentioned in Chapter 1, we are observing a data explosion which has motivated process industries, like manufacturing plants, to use these data to reduce the human load. This leads to increasing efficiency and productivity, and eventually minimizing manufacturing costs leading to higher profits. Chapter 1 also laid out various case studies where different industries are utilizing the power of data analytical platforms (IIOT), taking a step towards digital transformation. There were three main things summarized in this chapter as part of the Internet of Things, namely Digital Twin, Automated Quality Control, and Predictive Maintenance. In the next three chapters, we explained the theory behind each of these concepts and our work towards this.

Chapter 2 described our work towards developing analytical and predictive capabilities for a manufacturing process for the production of high performance containers. The objective was to gain a deeper understanding of the complex process with data coming from multiple sensors, to develop a hypothesis for causal relationships between variables, and to prove the hypothesis through a series of experiments and statistical testing. We also developed static model equations to provide analytical and predictive capabilities to the process. We deployed an automatic technique called Gaussian Bayesian Networks, a probabilistic method to quantify the relationships between variables for process modeling, optimization and control. Predictions from this model closely resembled the results from experiments carried out on the production line, thus developing a "Digital Twin" of the process.

Chapter 3 provided a proof-of-concept project for automated quality control using computer vision techniques. It described the theory behind the photo-elasticity experiments carried out for data collection as well as the Convolutional Neural Network model used for a binary classification task as good/bad products. We achieved an 88.9% accuracy using this approach. Recently this project was accepted for a patent application by the company. Continuing the path of digital transformation, Chapter 4 describes the advantage of Predictive Maintenance over React to Failure or Preventive Maintenance both for minimizing the costs for maintenance and downtime as well as providing the process engineers on the line the capability to predict failures. Here we described a few proof-of-concept projects to emphasize the power of this technique by utilizing the data from sensors or vibrational signals on mechanical equipment, as well as using data recorded by personnel, e.g., maintenance records, to predict the trend of failed components.

5.2 Future Work

Our work here is just a small step towards achieving "Industry 4.0" in the manufacturing sector. There is still a lot of scope for the improvement of these models like increasing the accuracy of these models, expanding its application to other sectors, exploring new problems which can be resolved through data driven tools and trying out new state-of the art techniques for a faster and better prediction. As mentioned in Chapter 2, we have a Bayesian Network structure in place with causal relationships between variables, this can act as a foundation over which multiple other algorithms like fault detection and root cause algorithm can be built. We have tried one simple approach towards this task by utilizing the co-variance matrix but has its own limitations which can be resolved with utilizing more advanced techniques like Neural Networks. We are in the process of developing such an approach. Furthermore, the convolutional neural network used in Chapter 3 is a simple architecture consisting of a few layers. We can further increase the accuracy by building a deeper network or hyper-tuning the parameters further with a larger image data-set. This was not possible due to data limitations. But once this is deployed on-line we can generate sufficient images to continuously improve the model, even with new changes to the faulty residual patterns. Lastly, predictive maintenance is a time-consuming task with multiple potential areas for improvement. We proposed a few strategies with very simple examples which are implemented in real-time. If enough funding and data are available, these tools can be implemented as a product capable of handling multiple tasks from data collection to dashboards providing process engineers and operators various insightful results, similar to the work carried out in Chapter 2. Moreover, research in this area is still nascent, with new machine and deep learning techniques, like the use of Reinforcement Learning, Auto-Encoders, etc. These algorithms are being developed and modified every few months. They will provide us with new ways to tackle the problem of PdM, as well as equipping us with a continuous strategy for improving model accuracy. We have barely scratched the surface of Industry 4.0, with considerable possibilities of using new technology in an increasingly data-driven world. There is a lot of ground left to explore!

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